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Determinants of Healthcare Data Analytics Adoption: The Moderating Role of Data Maturity and Organizational Culture

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Abstract

Health care data analytics is transforming the way medical services are delivered, managed, and improved. Every day, hospitals, clinics, laboratories, pharmacies, and wearable devices generate vast amounts of data that need to be transformed and analyzed. Thus, health care data analytics has become important for patients' well-being. The study developed and tested two direct and three moderating hypotheses. The study adopted a questionnaire from past studies using a five-point Likert scale. The sample size for the study was 350, which is appropriate for Smart PLS studies. We collected the data via a Google Form and focused on physicians and staff at the leading health care units in Karachi. We found support for all five articulated hypotheses. We accepted the Hypothesis stating that "IT infrastructure positively affects health care data analytics". The result also supported the Hypothesis that health care policies positively affect healthcare data analytics. We accepted the hypothesis stating "data integration positively affects health care data analytics." We found support for the hypothesis, which states "data integration positively affects healthcare data analytics. We also found support for the Hypothesis that states "Data growth maturity moderate IT infrastructure and health care data analytics." We also found support for the last hypothesis, which

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states “organizational culture moderate IT infrastructure and health care data analytics. All the accepted hypotheses align with prior studies and the literature.

Keywords: *Health care data analytics, IT infrastructure, health care policies, data integration, data growth maturity, and organizational behavior, Resource-Based View Theory, Social Technical Theory.*

Introduction

In both developing and developed countries, health care systems are undergoing rapid change due to digital transformation, exponential data growth, advances in information technology, and the demand for evidence-based decision-making (Aceto et al., 2020). Jarvenpaa (2020) asserts that health care organizations are now heavily dependent on health care data analytics. It enables the transformation of large, complex datasets into actionable insights that the organization uses to improve patient outcomes, operational efficiency, and strategic planning (Cozzoli et al., 2022). Many recent studies have documented that big data analytics has become an essential tool for health care delivery as it supports, predicts, and personalizes medicine approaches (Ngesimani et al., 2022). An HCDA is the foundation of IT infrastructure (Rajamani et al., 2021). Researchers believe that it ensures efficient data storage, processing power, interoperability, and system scalability (Faridoon & Kechadi, 2024). Most health care environments in Pakistan have limited capacity to integrate and analyze data efficiently due to various factors, including a fragmented system and legacy infrastructure (Wider et al., 2023). Zhang and Wang. (2025) believe that if health care organizations in developed and developing countries adopt advanced architectural data solutions, including data lakes and an integrated analytics platform, will increase their performance significantly (Rajamani et al., 2021).

Moreover, researchers believe that if firms adopt technological readiness, their health care policies and data analytics would increase profoundly (Zhang & Wang, 2025). Many recent studies have found that government, health care organizations, and institutional frameworks directly and indirectly enhance big data readiness and decision-making efficiency in healthcare systems (Cozzoli et al., 2022). Apart from the factors discussed above, organizational culture is another antecedent of HCDA implementation (Zhang et al., 2025). If a firm develops a data-driven culture, it would encourage employees to consider evidence-based insights, foster collaboration, and reduce resistance to technological change (Faridoon & Kechadi, 2024). Many past and recent empirical studies have documented that organizational culture is an important antecedent (Ngesimani et al., 2022). Aceto (2024) believes that the success of health care analytics depends significantly on data integration.

Many health care units are inefficient because they operate with siloed systems such as electronic health records (EHRs), laboratory systems, and insurance databases (Jarvenpaa & Essén, 2023). Firms' operations would improve if they could integrate these heterogeneous data sources. This integration would improve data accessibility and support clinical and administrative decision-making and health care outcomes (Ngesimani et al., 2022). Additionally, recent literature has documented that governance maturity is an important antecedent to health care analytics (Jarvenpaa & Essén, 2023). Firms without it may become inconsistent, insecure, and may not be able to interpret data efficiently (Wider et al., 2023).

Based on the above discussions, we have articulated the following objectives:

- 1 To ascertain “the effect of IT infrastructure on health care data analytics.”
- 2 To ascertain “the effect of health care policies on health care data analytics.”
- 3 To ascertain “the effect of data integration on health care data analytics.”
- 4 To ascertain “the moderating effect of data maturity on IT infrastructure and health care data analytics.”
- 5 To ascertain “the moderating effect of organizational culture on data integration and healthcare data analytics.”

Literature Review

Theoretical Underpinnings

The study has assimilated Resource-Based View Theory (RBV) (Wernerfelt, 1984), and Social Technical Theory (STS) (Trist & Bamforth, 1951).to develop a model that collectively explains how technological, organizational, and governance-related factors affect health care data analytics in health organizations in Karachi.

Resource-Based View (RBV)

The RBV Theory was coined in 1984. It postulates that strategic resources, such as analytics platforms, integration systems, data, and infrastructure, allow an organization to transform raw data into actionable knowledge (Cozzoli et al., 2022). Many recent studies have documented that an organization's infrastructure capabilities increase organizational analytics maturity and decision-making performance (Aceto et al., 2020).

Moreover, researchers believe that firms must not rely solely on IT infrastructure (Cozzoli et al., 2022). Its effectiveness depends on complementary organizational resources, including skilled personnel and supportive governance structures (Varadarajan, 2024). Moreover, researchers believe that health care units could be effective only if they can orchestrate technological and organizational assets (Dhrubo et al, 2024).

Socio-Technical Systems Theory (STS)

Socio-Technical Systems Theory was coined in 1951 (Trist & Bamforth, 1951). It postulates that social elements (i.e., people, culture, policies) (Govers & van Amelsvoort, 2023) and technical systems (i.e., IT infrastructure, data platforms) are highly interdependent (Iden & Bygstad, 2024). Many researchers, including Kemp et al. (2024), believe that the success of HCDA depends on two important factors: organizational culture and healthcare policies (Xu & Gao, 2024). These factors determine how data ought to be accessed, shared, and utilized (Ngesimani et al., 2022). Moreover, recent studies document that a strong data-driven culture is an important antecedent to the success of digital transformation (Iden & Bygstad, 2024). Additionally, researchers believe an effective digital transformation promotes data adoption, collaboration, and evidence-based decision-making (Rajamani et al., 2021). Conversely, effective health care policies define data governance boundaries, clarify interoperability standards, and clarify compliance requirements (Govers & van Amelsvoort, 2023). All these factors directly and indirectly affect the effectiveness of analytics (Ngesimani et al., 2022).

Hypothesis Development

Availability of IT Infrastructure and Healthcare Data Analytics

Successful implementation of health care data analytics, among other factors, significantly depends on the availability of information technology (Taipalus et al., 2023). Batko and Ślęzak (2022) have defined IT infrastructure as “technological resources that support data collection, storage, processing, integration, and dissemination within healthcare organizations.” Taipalus et al. (2023) state that technological resources encompass many components, including “hardware, software applications, databases, networking systems, cloud computing platforms, and electronic health record (EHR) systems.” (Yang et al., 2022). Moreover, researchers assert that healthcare organizations rely on data-driven decision-making; therefore, IT infrastructure is necessary to transform large volumes of healthcare data into actionable insights (Batko & Ślęzak, 2022; Taipalus et al., 2023).

Additionally, researchers believe that technological readiness is a critical determinant of organizational innovation (Kothari & Garg, 2019), and it is important from the

perspective of the Technology–Organization–Environment Framework (Balch et al., 2023). Moreover, firms with adequate and effective IT infrastructure are in a better position to capture, store, and process clinical and administrative data efficiently (Batko & Ślęzak, 2022). Additionally, increasing analytical capabilities significantly depends on factors such as advanced infrastructure that facilitates real-time data access and interoperability among information systems (Yang et al., 2022). Moreover, the Resource-Based Theory posits that competitors find it difficult to imitate valuable and rare organizational resources (Brossard et al., 2022). Furthermore, IT infrastructure is an important determinant of strategic organizational resources, as it helps in improving decision-making and health care outcomes (Brossard et al., 2022). Additionally, organizations can use analytical applications and generate insights from healthcare data if they possess a strong technological foundation (Khan & Khan, 2022).

Many recent studies have documented the importance of technological infrastructure in supporting data analytics initiatives (Berros et al., 2023). Moreover, researchers believe the effectiveness of healthcare units increases significantly if they have adequate infrastructure that supports data accessibility, system reliability, and information sharing (Kumar et al., 2023). On the contrary, health care units may be unable to manage large datasets, integrate information across departments, and deploy advanced analytical techniques if they lack adequate infrastructure (Khan & Khan, 2022). Based on the above discussions, we argue that healthcare units with adequate and effective IT infrastructure would have stronger healthcare data analytics capabilities than organizations with limited technological resources. (Batko & Ślęzak, 2022).

H1: Availability of "IT Infrastructure positively affects healthcare data analytics."

Healthcare Policies and Healthcare Data Analytics

Organizations with well-developed, structured policies are well-positioned to adopt and use healthcare data analytics (Batko & Ślęzak, 2022). Health care policy is a composite document containing laws, regulations, guidelines, and strategic initiatives developed by governments and healthcare authorities to improve healthcare delivery, patient safety, and data management (Balch et al., 2023). Many recent studies have noted that organizations seeking a favorable health care environment and the adoption of data analytics must focus on digital transformation, health information exchange, electronic health records, and interoperability standards (Berros et al., 2023). Moreover, researchers believe that evidence-based decision-making fosters an environment conducive to health care data analytics (Batko & Ślęzak, 2022). Furthermore, the Technology Organization–Environment (TOE) Framework influences organizational technology adoption (Yang et al., 2022), and implementation of advanced analytics systems in an

organization. According to TOE framework provide the necessary regulatory foundation for health care organizations. This supports investment in data infrastructure and data governance mechanisms, as well as the implementation of advanced analytics systems (Batko & Ślęzak, 2022). Health organizations with supportive policies are encouraged to use data-driven approaches to improve clinical outcomes, operational efficiency, and resource allocation (Berros et al., 2023). Moreover, such policies analyze health care data more effectively by promoting standardization, which allows firms to collect, share, and analyze data (Balch et al., 2023).

The availability and quality of health care data depend profoundly on regulatory initiatives related to electronic health records, data privacy, cybersecurity, and health information exchange (Berros et al., 2023). These factors directly and indirectly affect the successful implementation of analytics (Batko & Ślęzak, 2022). Moreover, the policy framework enables health care providers to monitor performance indicators, thereby supporting evidence-based decision-making (Berros et al., 2023). Many recent studies have documented that supportive healthcare policies (Balch et al., 2023), facilitate digital health transformation (Yang et al., 2022) by reducing implementation barriers (Balch et al., 2023) and encouraging organizational investments in data technologies (Batko & Ślęzak, 2022). Brossard et al. (2022) assert that analytic adoption is difficult under a policy framework that is unclear, weak, and insufficiently supported. In contrast, analytics adoption is comparatively easier when supported by clear, well-articulated plans and organizational support (Berros et al., 2023). A favorable policy environment also helps developing and adopting healthcare analytics capabilities (Yang et al., 2022). On the contrary, an adverse policy environment does not facilitate the adoption of health care analytics capabilities (Balch et al., 2023).

H2: Healthcare policies “positively affect Healthcare Data Analytics.”

Data Integration and Healthcare Data Analytics

Data integration technical capabilities are an important determinant of health care data analytics (Batko & Ślęzak, 2022). It involves combining data from multiple sources, including electronic health records, laboratory and pharmacy systems and administrative databases, for effective health care data analytics (Balch et al., 2023). Researchers believe that data integration is necessary for comprehensive analysis and informed decision-making (Berros et al., 2023). This is important as in most health organizations, data is often fragmented across different departments and systems (Khan et al., 2022). Many studies, while extending the Technology–Organization–Environment (TOE) framework, documented that technological characteristics such as system integration and interoperability play a crucial role in the success of analytics adoption (Taipalus

et al., 2023). Moreover, organizations with weak data integration capabilities cannot consolidate patient information across multiple systems. (Yang et al., 2022). On the contrary, organizations with strong data integration capabilities are better equipped to consolidate patient information across multiple systems. Furthermore, data integration is important for an organization, as it reduces data silos that adversely affect health care data analytics (Berros et al., 2023). Extending this argument, researchers have asserted that data stored in disconnected systems reduces data visibility and quality (Balch et al., 2023). On the contrary, a highly integrated system has several advantages, including data consistency, reduced redundancy, and enhanced reliability of analytics outputs (Khan et al., 2022). Furthermore, researchers believe that a well-integrated system is necessary for real-time data processing, which is necessary for predictive modeling, clinical decision support systems (Taipalus et al., 2023).

Many recent studies have documented that interoperability and data integration support healthcare digital transformation and the development of analytics capabilities (Yang et al., 2022). Additionally, recent studies have also noted that integrated health information systems increase data accessibility and seamless data exchange (Batko & Ślęzak, 2022). These factors directly and indirectly affect health care data analytics (Khan et al., 2022). Moreover, data integration helps in the development of a unified data architecture, which is essential for the organization to analyze big data effectively (Taipalus et al., 2023). Furthermore, integrated datasets enable firms to employ advanced techniques such as machine learning and artificial intelligence (Yang et al., 2022). These advanced techniques are essential for improved data accuracy and reliability, which enhances decision-making capabilities in a health care organization (Batko & Ślęzak, 2022).

H3: Data Integration “positively affects healthcare data analytics.”

IT Infrastructure, Data Governance Maturity, and Healthcare Data Analytics

According to Brossard et al. (2022), data governance maturity refers to defined policies, procedures, roles, and standards for managing data as a strategic asset (Abraham et al., 2019). It includes data ownership, data accessibility, compliance, lifecycle management, and data quality management practices (Khan et al., 2022). Researchers believe that in a health care organization, data is highly sensitive and generated from multiple clinical and administrative systems (Ngesimani et al., 2022). Therefore, a well-governed structure is essential to ensure that data is accurate, secure, and usable for analytics purposes (Langer, 2025). Moreover, many researchers have noted that the technological foundation for health care data analytics helps in data storage, processing, integration, and access (Taipalus et al., 2023). At the same time, the technical foundation significantly

depends on the availability of information technology (Zhang & Wang, 2025). However, researchers have observed that the mere availability of IT infrastructure does not produce effective analytics outcomes (Abraham et al., 2019). It depends significantly on how an organization manages, standardizes, and governs its IT infrastructure (Brossard et al., 2022). However, firms with mature governance can effectively utilize and generate reliable, meaningful insights from their IT infrastructure (Khan et al., 2022). In contrast, immature governance cannot effectively generate reliable and meaningful insights from IT infrastructure (Langer, 2025).

Moreover, technological resources, including IT infrastructure, interact with organizational capabilities to determine the outcomes of technological utilization (Ngesimani et al., 2022). At the same time, organizational governance mechanisms help determine how effective technological resources translate into analytical capabilities (Taipalus et al., 2023). Furthermore, health organizations with a mature governance framework can enhance the effectiveness of IT infrastructure in supporting healthcare data analytics (Zhang & Wang, 2025). Additionally, organizations with a mature governance structure are better positioned to implement standardized data definitions, integrated data architectures, and robust data quality controls (Abraham et al., 2019). Additionally, such an organization has greater capacity to implement standardized data definitions, integrate data architectures, and implement robust data quality controls (Brossard et al., 2022). Moreover, such organizations can reduce data fragmentation and improve data-driven insights (Taipalus et al., 2023). These aspects allow firms to use data analytics for decision-making (Zhang & Wang, 2025). Conversely, organizations with a weak governance structure may face inconsistent data, poor data quality, and limited data accessibility, which reduce the benefits of IT infrastructure (Khan et al., 2022). Many recent studies have documented that data governance is an essential determinant of successful health care analytics (Langer, 2025). Moreover, studies have noted that firms with effective governance practices can ensure data reliability, facilitate interoperability between systems, and ensure compliance with healthcare regulations (Brossard et al., 2022).

H4: Data governance maturity “moderates the relationship between availability of IT infrastructure and healthcare data analytics.”

IT Infrastructure, Organizational Culture, and Healthcare Data Analytics

Organizational culture helps individuals understand how to behave toward one another and make decisions (Brossards et al., 2022). It includes shared values, beliefs, norms, and practices (Batko & Ślęzak, 2022). In the context of a health organization, organizational culture is critical to determining how individuals perceive, adopt, and

use technological resources (Tortorella et al., 2022). In addition, culture plays a pivotal role in understanding and using technological resources (Mikalef et al., 2020). Firms that promote a culture of innovation, collaboration, and learning create an environment where individuals develop the capabilities to use healthcare data analytics (Kraus et al., 2021). Moreover, when information technology infrastructure is available, it provides the essential technological foundation for healthcare data analytics, enabling them to store, integrate, process, and access data (Kitsios & Kapetaneas, 2022). However, just the mere presence of an IT structure does not mean the data is being utilized effectively (Bilgiç & Camgoz, 2023). It significantly depends on the organizational environment that promotes data analytics (Brossards et al., 2022).

Additionally, within a technology organization's environment, a health care organization can play a key role in enhancing technological capabilities and organizational outcomes (Batko & Ślęzak, 2022). Moreover, research indicates that if an organization fosters a supportive, data-driven culture, it will motivate employees to invest in analytics infrastructure, encourage cross-functional collaboration, and promote the integration of data into decision-making. (Tortorella et al, 2022). Moreover, in such a conducive environment, individuals would be highly motivated to actively engage with analytical tools and leverage the available infrastructure (Mikalef et al., 2020). As a result, it would generate insights that improve clinical and operational performance (Kraus et al., 2021). In contrast, a non-conductive environment, despite a well-developed IT structure, may not be able to improve clinical and operational performance. The factors that contribute to this underutilization of IT infrastructure include limited employee engagement, low data literacy, or resistance to change (Kitsios & Kapetaneas, 2022).

H5: Organizational culture “positively moderates the relationship between data integration of IT infrastructure and healthcare data analytics.”

Conceptual Framework

Using the above theoretical and empirical discussions, we have developed a conceptual framework. It has three direct and two moderating hypotheses, depicted in Figure 1.

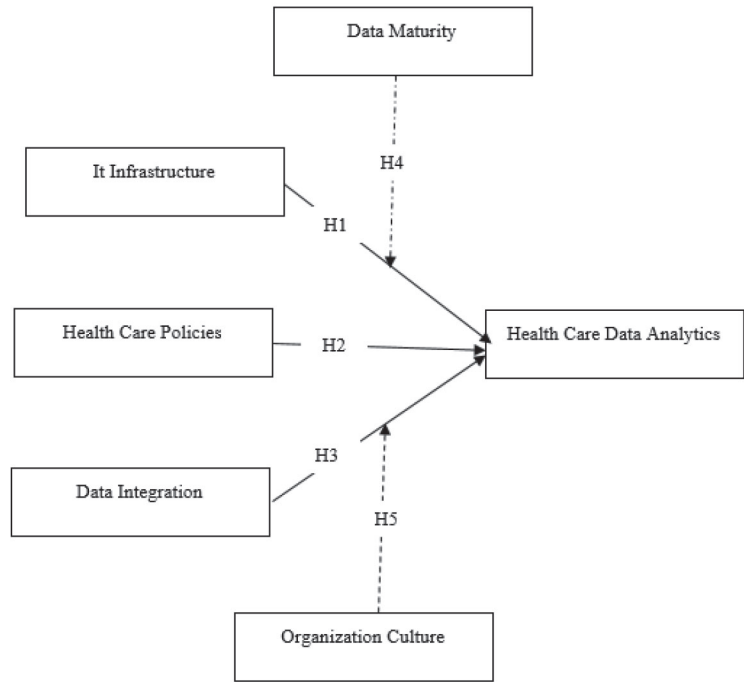


Figure 1: Conceptual Framework

Methodology

Research Design

The study used a quantitative research approach to examine the three direct and two moderating hypotheses (Creswell & Creswell, 2018). This research technique has several benefits. It reduces personal biases (Sekaran & Bougie, 2019) as it relies on numerical and statistical data (Trochim & Arora, 2016). It is recommended with a quantitative study, other researchers can replicate the study and verify the results (Creswell & Creswell, 2018). The study adopted a cross-sectional survey design in which researchers collected the data at a single point in time (Trochim & Arora, 2016). This research design helps analyze the respondents' perceptions of technological, organizational, and governance factors (Sekaran & Bougie, 2019).

The philosophical approach is positivism. It is commonly used in social science studies in which researchers assume that reality is objective and can be measured using structured instruments (Kothari & Garg, 2019). This study, based on existing theory, developed a hypothesis that was empirically tested; thus, it falls under a deductive approach (Kothari & Garg, 2019). It used Smart PLs for data analysis, as it is suitable for

complex models such as this one, which has many direct and moderating relationships (Cohen & Morrison, 2018).

Population and Sampling

The population is all the elements in a population (Creswell & Creswell, 2018). The population for this study is all healthcare employees working in the healthcare units in Karachi. A sample is a small segment of the population from which researchers draw inferences about the population (Trochim & Arora, 2016). The sample size for this study was 200, which, according to many researchers, is appropriate for Smart PLS data analysis (Sekaran & Bougie, 2019). However, we distributed 400 questionnaires and received 350 filled in questionnaires.

Sampling Techniques

Researchers have divided sampling techniques into two broad categories. Probability sampling in which each element has an equal and calculated chance of being selected (Kothari & Garg, 2019). In this technique, a sample frame is required (Cohen & Morrison, 2018). In non-probability sampling, the chances of the element's being selected are not known, nor can be calculated (Creswell, 2015). The study used convenience sampling because the sampling frame was unavailable (Yin, 2018). We collected data based on an online survey. This technique allows researchers to reach the audience at low cost (Gravetter & Forzano, 2018).

Ethical Considerations

In social science studies, when collecting primary data, it is necessary to follow ethical protocols (Creswell & Creswell, 2018). The ethical standards call for the protection of participants' rights and privacy (Trochim & Arora, 2016). Before the survey, we informed participants of the study's purpose and objectives (Creswell & Creswell, 2018). They were also informed that participation in the survey is not mandatory and that they can withdraw at any time during the process (Sekaran & Bougie, 2019). We ensured the confidentiality and anonymity of the respondents by not collecting any personally identifiable information (Kothari & Garg, 2019).

Common Method Bias

Data collected may suffer from common method bias, which may either give inflated or deflated results (Creswell & Creswell, 2018). It occurs when a researcher collects data from a single source (Trochim & Arora, 2016). Researchers believe this bias occurs when variations in responses are attributed to the measurement method rather than to the constructs being measured (Sekaran & Bougie, 2019). To reduce the occurrence of common method bias, we adopted a questionnaire used in prior studies and assessed

its reliability and validity, as it was developed in countries with cultures that differ from Pakistan's (Kothari & Garg, 2019). In addition, we applied Harman's single-factor test; the results showed that no single factor explained more than 50% of the variance, suggesting that it was not infected with common method bias (Yin, 2018).

Scale and Measures

The study adopted the questionnaire used in previous studies. It was based on a 5-point Likert scale. One showing low agreement, and five showing a high agreement. We used five points because researchers have documented that respondents find it easier to fill such questionnaires. Table 1 shows the constructs used in the questionnaire, their sources, and the number of items.

Table 1: Scale and Measures

Constructs	Sources	Items
Availability of IT Infrastructure	Kim et al. 2021	5
Health Care Data Analytics	Ślęzak (2022)	5
Organization Culture	Alharbi et al. (2021)	5
Health Care Policies	Yang et al. (2022)	5
Data Integration	Balch et al. (2023)	5
Data Governance Maturity	Abraham et al. (2019)	5

Results

Respondent profile

We have presented the respondents' profiles in Table 2. It is important because it shows the background information about the respondents (Sekaran & Bougie, 2019). Moreover, it helps respondents understand who contributed in the survey (Kothari & Garg, 2019).

Table 2: Respondent Profile

Demographic Variable	Categories	Percentage (%)
Gender	Male	58%
	Female	42%
Age	21–30 years	30%
	31–40 years	45%
	41–50 years	20%
	Above 50 years	5%

Education Level	Diploma/Other	15%
	Bachelor’s Degree	50%
	Master’s Degree	35%
Professional Role	Clinicians	40%
	IT Managers	40%
	Hospital Administrators	25%
	Data Information Officers	20%
Work Experience	1–5 years	40%
	6–10 years	30%
	11–15 years	20%
	More than 15 years	10%

Descriptive Analysis

Table 3 presents descriptive statistics, including mean, standard deviation, skewness, kurtosis, and Cronbach's Alpha values. The Table shows that the Skewness and Kurtosis values range between ± 2.5 and Cronbach's Alpha values >0.70 , suggesting that the constructs used in the study fully meet the requirements of univariate normality (Morera & Stokes, 2016) and internal consistency (Taber, 2018).

Table 3: Descriptive Analysis

Construct	Mean	SD	Skewness	Kurtosis	Cronbach’s Alpha
Avail. of IT Infrastructure	3.78	0.71	-0.42	0.18	0.86
Healthcare Policies	4.02	0.65	-0.51	0.37	0.90
Organizational Culture	3.69	0.74	-0.24	0.10	0.84
Data Integration	3.85	0.69	-0.36	0.22	0.88
Data Governance Maturity	3.67	0.73	-0.19	-0.05	0.83
Healthcare Data Analytics	4.06	0.62	-0.58	0.41	0.91

Measurement Model

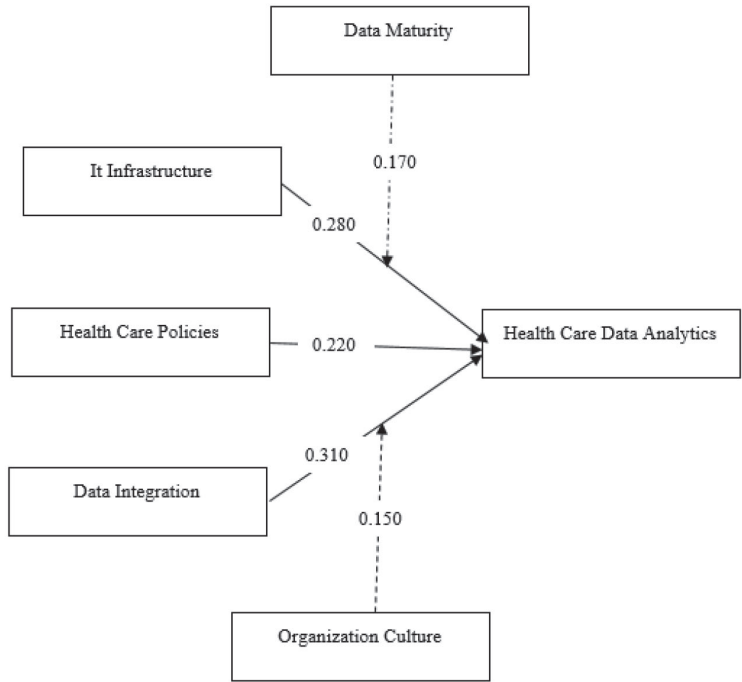


Figure 2: Measurement Model

Convergent Validly

Convergent validity determines “the extent to which the indicator variables of each construct correlate and measure the underlying concept” (Cizek2020). Table 4 presents a summary of the results. It shows that the factor loadings for all constructs are greater than 0.70, the AVE values are greater than 0.50, and the composite reliability is greater than 0.70 (Gonzalez et al., 201). All these values exceed the recommended threshold(Cizek2020). Thus, we have inferred that a theoretical association between the constructs and their indicator variables exists (Raykov et al., 2020).

Table 4: Convergent Validity

Construct	Item	Factor Loading	Composite Reliability	AVE
Availability of IT Infrastructure	ITI1	0.81	0.87	0.62
	ITI2	0.84		
	ITI3	0.78		
	ITI4	0.76		

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Healthcare Policies	HP1	0.86	0.91	0.68
	HP2	0.88		
	HP3	0.82		
	HP4	0.80		
Organizational Culture	OC1	0.79	0.88	0.64
	OC2	0.83		
	OC3	0.81		
	OC4	0.78		
Data Integration	DI1	0.85	0.90	0.66
	DI2	0.87		
	DI3	0.82		
	DI4	0.80		
Data Governance Maturity	DGM1	0.80	0.86	0.61
	DGM2	0.83		
	DGM3	0.77		
	DGM4	0.75		
Healthcare Data Analytics	HDA1	0.88	0.92	0.70
	HDA2	0.90		
	HDA3	0.86		
	HDA4	0.84		

Discriminant Validity

Researchers assert that it is necessary to assess discriminant validity before testing the hypothesis (Hair et al. 2022); otherwise, the results may be inflated or deflated (Hair et al 2019). Table 5 shows the results based on Fornell and Larcher (1991) criterion. It shows “Square root of Ave values are greater than the correlation values” (Fornell & Bookstein,1982), suggesting the "constructs are distinct and empirically different” (Kline, 2023).

Table 5: Discriminant Validity (Fornell and Larcher (1991))

Constructs	AIT	HCP	OC	DI	DGM	DGM
Availability of IT Infrastructure	0.79					
Health Care policies	0.52	0.82				
Organizational Culture	0.48	0.50	0.80			
Data Integration	0.55	0.57	0.54	0.81		
Data Governance Maturity	0.46	0.49	0.51	0.52	0.78	
Health Care Data Analytics	0.60	0.63	0.58	0.66	0.56	0.84

Discriminant Validity (HTMT Ratio)

In addition to discriminant validity assessed using Fornell and Larcker's (1981) criterion, we also assessed discriminant validity using the HTMT ratio (Henseler et al., 2015). The reason for ascertaining discriminant validity based on the HTM ratio is: (1) The Fornell-Larcker may show acceptable discriminant validity even if two constructs are highly similar (Hair et al., 2022). Comparatively, researchers believe the HTMT ratio is "more sensitive and better at identifying when constructs are not truly distinct" (Hair et al, 2019). Table 6 shows that all HTMT ratio values are below 0.85, suggesting that the constructs used in the study are distinct and empirically different" (Kline, 2023).

Table 6: Discriminant Validity

Constructs	AIT	HCP	OC	DI	DGM	HCDA
Availability of IT Infrastructure	—					
Health Care policies	0.74	—				
Organization Culture	0.69	0.72	—			
Data Integration	0.76	0.78	0.75	—		
Data Governance Maturity	0.81	0.84	0.79	0.86	—	
Health Care Data Analytics	0.66	0.70	0.73	0.71	0.74	—

Fit Indices

Model fit indices show how well the proposed measurement model fits the observed variable (Hu & Bentler, 1999). Table 7 shows the results of different fit indices (Kline, 2023). SRMR indices is <0.08 and NFI indices is greater than 0.90, suggesting a good fit (Hair et al., 2019), and dULS and dG values indicate acceptable fit levels (Byrne, 2016).

Table 7: Fit Indices

Fit Index	Value	Recommended Threshold	Interpretation
SRMR	0.062	< 0.08	Good fit
d_ULS	0.71	Lower is better	Acceptable fit
d_G	0.48	Lower is better	Acceptable fit
NFI (Normed Fit Index)	0.91	> 0.90	Good fit
Chi-Square	412.5	Lower is better	Acceptable fit
RMS_theta	0.085	< 0.12	Good fit

R and Q Squared Values

The researcher asserts that R^2 (coefficient of determination) and Q^2 (predictive relevance) (Hair et al., 2022) are important because they measure different aspects of model performance (Hair et al., 2022). We found the R-squared value is 0.42, which suggests the model explains a moderate amount of variance in the endogenous

construct (Geisser, 1974). Similarly, we found the Q-squared value is 0.64, suggesting the model has adequate predictive relevance (Hair et al., 2022).

Hypothesis Results

The study has tested three direct and two moderating hypotheses. We found support for all five Hypotheses. The results are depicted in Table 8.

Table 8: Hypothesis Results

Relationship	Beta (β)	T-Value	P-Value	Results
IT Infra. → Health Care Data Analytics (H1)	0.280	4.120	0.000	Supported
Health Care Policies → H. Care Data Analytics(H2)	0.220	3.450	0.001	Supported
Data Integration → H.Care Data Analytics (H3)	0.310	4.670	0.000	Supported
IT Infra.× Data G. Maturity → H. C. Data Analytics(H4)	0.170	2.890	0.004	Supported
IT Infra. × Org.Culture → H. C. Data Analytics (H5)	0.150	2.560	0.011	Supported

The results in the above Table show that the highest effect size was in Hypothesis 3: "Data integration positively affects health care data analytics" ($\beta= 0.310$, $t=4.670 <0.05$) and the lowest was on the moderating effect on Hypothesis 5: "Data maturity moderates IT ultrastructure and healthcare data analytics ($\beta= 0.150$, $t=2.560 <0.05$).

Discussion and Conclusion

Discussion

We accepted Hypothesis 1: "IT infrastructure positively affects health care data analytics." Successful implementation of health care data analytics, among other factors, significantly depends on the availability of information technology (Taipalus et al., 2023). Batko and Ślęzak (2022) have defined IT infrastructure as "technological resources that support data collection, storage, processing, integration, and dissemination within healthcare organizations." Kothari and Garg (2019) states that technological resources encompass many components, including "hardware, software applications, databases, networking systems, cloud computing platforms, and electronic health record (EHR) systems." (Yang et al., 2022). Many researchers assert that healthcare organizations rely on data-driven decision-making; therefore, IT infrastructure is necessary to transform large volumes of healthcare data into actionable insights (Batko & Ślęzak, 2022; Taipalus et al., 2023). Moreover, researchers believe that technological readiness is a critical determinant of the adoption of organizational innovation (Kothari & Garg, 2019). It is important from the perspective of the Technology–Organization–Environment Framework (Balch et al., 2023). Moreover, firms effective in IT infrastructure are in better positioned to capture, store, and process clinical and administrative

data efficiently (Taipalus et al., 2023). Additionally, increasing analytical capabilities significantly depends on factors such as advanced infrastructure that facilitates real-time data access and interoperability among information systems (Yang et al., 2022). Moreover, the Resource-Based Theory posits that competitors find it difficult to imitate valuable and rare organizational resources (Brossard et al., 2022). Furthermore, IT infrastructure is an important determinant of strategic organizational resources, enabling health care units to use analytical tools and technologies to improve decision-making, operate more efficiently, and improve patient health care outcomes (Brossard et al., 2022). Additionally, organizations can use analytical applications and generate insights from healthcare data if they possess a strong technological foundation (Khan & Khan, 2022).

Our result supports Hypothesis 2: "Health care policies positively affect health care data analytics." Technological resources, including IT infrastructure, interact with organizational capabilities to determine the outcomes of technological utilization (Ngesimani et al., 2022). At the same time, organizational governance mechanisms help determine how effective technological resources translate into analytical capabilities (Taipalus et al., 2023). Moreover, health organizations with a mature governance framework can enhance the effectiveness of IT infrastructure in supporting healthcare data analytics (Zhang & Wang, 2025). Furthermore, organizations with a mature governance structure are better positioned to implement standardized data definitions, integrated data architectures, and robust data quality controls (Abraham et al., 2019). Additionally, such an organization has greater capacity to implement standardized data definitions, integrate data architectures, and implement robust data quality controls (Brossard et al., 2022).

We found support for Hypothesis 3: "Data integration positively affect data care health analytics." Many recent studies have documented that interoperability and data integration support healthcare digital transformation and the development of analytics capabilities (Yang et al., 2022). Additionally, recent studies have also noted that integrated health information systems increase data accessibility and seamless data exchange (Batko & Ślęzak, 2022). These factors directly and indirectly affect health care data analytics (Khan et al., 2022). Moreover, data integration helps in the development of a unified data architecture, which is essential for the organization to analyze big data effectively (Taipalus et al., 2023). Furthermore, integrated datasets enable firms to employ advanced techniques such as machine learning and artificial intelligence (Yang et al., 2022). These advanced techniques are essential for improved data accuracy and reliability, which enhances decision-making capabilities in a health care organization (Batko & Ślęzak, 2022).

We accepted Hypothesis 4: "Data growth maturity moderates the relationship between IT infrastructure and health care data analytics" Technological resources, including IT

infrastructure, interact with organizational capabilities to determine the outcomes of technological utilization (Ngesimani et al., 2022). At the same time, organizational governance mechanisms help determine how effective technological resources translate into analytical capabilities (Taipalus et al., 2023). Moreover, healthcare organizations with a mature governance framework can enhance the effectiveness of IT infrastructure in supporting healthcare data analytics (Zhang & Wang, 2025). Furthermore, organizations with a mature governance structure are better positioned to implement standardized data definitions, integrated data architectures, and robust data quality controls (Abraham et al., 2019). Additionally, such an organization has greater capacity to implement standardized data definitions, integrate data architectures, and implement robust data quality controls (Brossard et al., 2022). Furthermore, such organizations can reduce data fragmentation and improve data-driven insights (Taipalus et al., 2023). These aspects allow firms to use data analytics for decision-making (Taipalus et al., 2023). Conversely, organizations with a weak governance structure may face inconsistent data, poor data quality, and limited data accessibility, which reduce the benefits of IT infrastructure (Khan et al., 2022). Many recent studies have documented that data governance is an essential determinant of successful health care analytics (Langer, 2025). Moreover, studies have noted that firms with effective governance practices can ensure data reliability, facilitate interoperability between systems, and ensure compliance with healthcare regulations (Brossard et al., 2022).

We accepted Hypothesis 5: "Organizational culture moderates the relationship between IT infrastructure and health care data analytics." When information technology infrastructure is available, it provides the essential technological foundation for healthcare data analytics, enabling individuals to store, integrate, process, and access data (Kitsios & Kapetaneas, 2022). However, just the mere presence of an IT structure does not mean the data is being utilized effectively (Bilgiç & Camgoz, 2023). It significantly depends on the organizational environment that promotes data analytics (Brossards et al., 2022). Additionally, a technology organization's environment, allows a health care organization in enhancing and organizational outcomes (Batko & Ślęzak, 2022). Moreover, research indicates that if an organization fosters a supportive, data-driven culture, it will motivate employees to invest in analytics infrastructure, encourage cross-functional collaboration, and promote the integration of data into decision-making. (Tortorella et al, 2022). Additionally, in such a conducive environment, individuals would be highly motivated to actively engage with analytical tools and leverage the available infrastructure (Mikalef et al., 2020). As a result, it would generate insights that improve clinical and operational performance (Kraus et al., 2021). In contrast, a non-conductive environment, despite a well-developed IT structure, may not remain underlined. The factors that contribute to this underutilization of IT infrastructure include limited employee engagement, low data literacy, or resistance to change (Kitsios &

Kapetaneas, 2022). Many past studies have documented that a conducive organizational culture may enhance the relationship between IT infrastructure availability and healthcare data analytics (Bilgiç & Camgoz, 2023). In contrast, a non-conductive organizational culture may weaken the association between the availability of IT infrastructure and healthcare data analytics (Tortorella et al, 2022).

Conclusion

Hospitals and health clinics generate a large amount of data daily (Tortorella et al, 2022). It includes diagnostic results, treatment histories, insurance claims, and real-time health monitoring data (Cohen & Morrison, 2018). Researchers assert that in view of this vast data, hospitals and health care units use IT infrastructure to organize and analyze this information to make improved decisions and patient outcomes (Khanra et al., 2020). This is only possible if health care organizations use health care data analytics to convert raw data into meaningful insight (Imran et al., 2021). Additionally, data analytics help physicians detect high-risk diseases, including diabetes and heart disease (Piovani, Bonovas, 2022). Given the importance of healthcare data analytics, we have developed a conceptual framework that has three independent variables (i.e., IT infrastructure, healthcare policies, and data integration). Two moderating variables (i.e., data maturity and organizational culture) and an independent variable (i.e., health care data analytics). These variables were used to develop and test five hypotheses. Three direct and two moderating relationships. The study adopted a questionnaire from past studies using a five-point Likert scale (Creswell & Creswell, 2018). The sample size for the study was 350, which is appropriate for Smart PLS studies (Cohen & Morrison, 2018). We collected the data via a Google Form and focused on physicians and staff at the leading health care units in Karachi. We found support for all five articulated hypotheses. We accepted the Hypothesis1: "IT infrastructure positively affects health care data analytics". The result also supported the Hypothesis 2: "Health care policies positively affect healthcare data analytics". "We found support for the Hypothesis 3: "data integration positively affects healthcare data analytics. We also found support for the Hypothesis 4 "Data maturity moderate IT infrastructure and health care data analytics." We also found support for the Hypothesis 5: "Organizational culture moderate IT infrastructure and health care data analytics. All the accepted hypotheses align with prior studies and the literature.

Implications

This study has several theoretical and practical implications. The study has assimilated two theories: Resource-Based and Social Technological System (Alharthi et al., 2020) to find how the antecedents and moderators affect health care data analytics. Based on the Resource-Based Theory, we have concluded that IT infrastructure alone is insufficient to enhance health care data analytics (Mikalef et al., 2020). Its significance strongly depends on whether it is supported by complementary resources, including data integration capabilities

and governance maturity (Taipalus et al, 2023). Additionally, the study has advanced Social System Theory (STS) (van de-Wearing et al., 2021) by confirming that organizational culture and health policies enhance the effectiveness of technological systems (Piovani et al., 2020). The study findings extend the Dynamic Capabilities Theory (Alharthi et al., 2020) by suggesting that data governance and data integration allow health care organizations to adopt, integrate, and optimize data resources (Taipalus et al, 2023).

The study documents that organizational culture is important in healthcare organizations. Therefore, we suggest organizations must foster a data-driven culture. For this purpose, the management of a health care organization should provide ongoing training on change management initiatives and encourage employees to make evidence-based rather than random decisions (Ezerins et al., 2022). We believe an advanced analytics system is bound to fail without cultural readiness (Lebaea et al., 2024). Moreover, we believe that policymakers, while articulating health care policies, ensure that regulatory frameworks promote data standardization, interoperability, and secure data sharing (Perlin et al., 2016). We found the moderating role of data governance maturity. Thus, we suggest that healthcare organizations should establish a strong governance framework (Lebaea et al., 2024). A strong governance framework includes data quality management, stewardship roles, and compliance monitoring systems (Perlin et al., 2016). We also believe the organizations should not invest in technology in isolation (Lebaea et al., 2024). They must adopt a balanced approach in which infrastructure development, governance maturity, and cultural transformation progress simultaneously to maximize HCDA effectiveness (Taipalus et al, 2023).

Limitation and Future Research

This study examined three antecedents: IT infrastructure, health care policies, and data integration. Future studies may examine other antecedents, including the medical coding system, Biostatistics, and the HITECH Act. We used two moderators in the study: organizational culture and data growth maturity. Future studies may use other moderators, including Data governance and top management's support for digital transformation readiness. The study used a quantitative approach and collected data through a structured questionnaire. Future studies may use qualitative or mixed methods. We collected data using a Google Form; other studies may collect data physically. The sample size for this study was small, and we focused on a single city. Future studies may collect the data with a larger sample and in other cities. We focused on the top health care units in Karachi; other studies may focus on health care units in the public or private sectors. We collected data using convenience sampling; future studies may use probability sampling in their studies.

Annexure 1

Constructs and Items Used in the Question

Availability of IT Infrastructure

1. Our organization has adequate IT infrastructure for data processing.
2. We have sufficient hardware and software for healthcare data management.
3. Our systems support real-time data access.
4. Cloud computing resources are available in our organization.
5. Our IT infrastructure supports data analytics activities.

Healthcare Data Analytics

1. Our organization uses data analytics for decision-making.
2. We utilize predictive analytics in healthcare operations.
3. Data is used to improve patient outcomes.
4. Analytical tools are integrated into workflows.
5. Data insights support managerial decisions.

Organizational Culture

1. Our organization encourages data-driven decisions.
2. Innovation is supported in our workplace.
3. Employees are encouraged to use data in decision-making.
4. Knowledge sharing is promoted.
5. Leadership supports analytics adoption.

Healthcare Policies

1. Our policies support healthcare digitalization.
2. Our regulations encourage the use of data analytics.
3. Our organization complies with healthcare data policies.
4. Policy environment aligns with our organization's culture.
5. Our Standards support data sharing and data analytics.

Data Integration

1. Our systems integrate data from multiple departments.
2. Clinical and administrative data are well integrated.
3. Data is easily shared across systems.
4. We have interoperable information systems.
5. Data integration supports analytics processes.

Data Governance Maturity

1. Our organization has clear data governance policies.
2. Data quality is regularly monitored.
3. Data ownership roles are clearly defined.
4. Data security policies are strictly followed.
5. Data is managed according to standards and regulations.

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